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Land use and land cover changes and their effect on forest cover dynamics: A CA–ANN model in East Khasi Hills, Meghalaya, India

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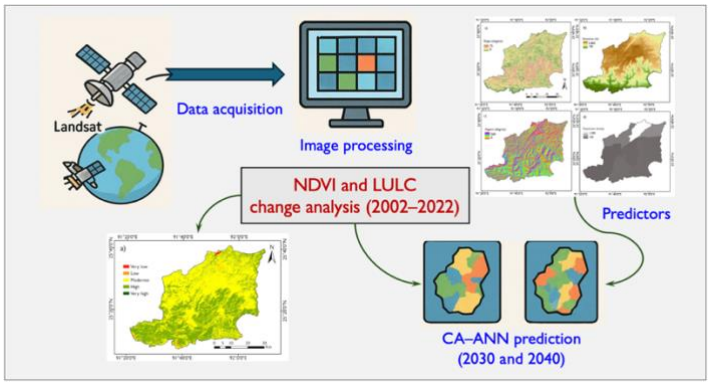

Highlights

- *We analyzed the impact of LULC changes on forest cover dynamics.*
- *LULC change detection revealed a growing trend in built-up areas.*
- *Dense forests have been converted into moderate forests due to human activities.*
- *Forest cover is projected to decrease steadily from 51% in 2022 to 41% by 2040.*

Abstract

Land use and land cover (LULC) changes, driven by urbanization and human activities, play an important role in forest cover dynamics. Understanding the interactions of these factors is essential for addressing environmental impacts and formulating sustainable policies for forest management. This study investigated the effects of urbanization on LULC changes from 2002 to 2022 using support vector machine (SVM) algorithm in East Khasi Hills, Meghalaya, India. Landsat 7 ETM+ imagery from 2002 and Landsat 8 OLI/TIRS imagery from 2013 and 2022 were used in this study. Seven land use classes, dense forest, moderate forest, sand bar, fallow land, settlement, water body, and agriculture were categorized. Dense forest has declined by 33 km^2 from 2002 to 2022, indicating persistent deforestation. Moderate forest expanded until 2013 but declined later in 2022, suggesting degradation. Agricultural land increased gradually by 157 km^2 from 2002 to 2022, likely due to shifting cultivation and land reclamation. Water bodies exhibited a minor fluctuation, while fallow land declined by 85 km^2. Sand bars remained stable, showing only a minor change, suggesting minimal sedimentation effects. The results suggest the gradual expansion of built-up areas by 30 km^2, along with the increase in agricultural lands. The predicted LULC changes for 2030 and 2040 indicate

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ongoing deforestation and rapid expansion of settlements. A comprehensive study with additional data is needed to help policymakers, particularly those responsible for forest management in the East Khasi Hills, to better understand LULC changes and their impact on forest cover dynamics.

1 Introduction

Forests are among the most essential natural resources and serve as habitats for diverse flora and fauna (Abedi Gheshlaghi, 2019; Tadese et al., 2020; Sivrikaya and Küçük, 2022; Sarkissian and Kutia, 2024). They help maintain ecological stability and biodiversity and enhance environmental quality by reducing soil erosion, increasing water retention, and balancing hydrological and biogeochemical processes. Additionally, forests provide a wide range of economic, sociological, and cultural services (Sarkissian and Kutia, 2024). Therefore, it is crucial to protect forests and ensure sustainable management of these natural resources for environmental stability.

The Normalized Difference Vegetation Index (NDVI) has been extremely useful for forest cover monitoring, vegetation cover, and predicting plant health (Almouctar et al., 2020; Mehmood et al., 2024). It assists in extracting forest areas, facilitating spatial and temporal monitoring. Several studies have effectively adopted NDVI for forest monitoring and vegetation growth status (Kumar et al., 2007; Saikia, 2009; Gandhi et al., 2015; Zaitunah et al., 2018; Islam et al., 2021; Giridharan and Sivakumar, 2022; Prăvălie et al., 2022). These studies have highlighted the use of NDVI in detecting vegetation stress, assessing land degradation, and tracking changes in vegetation patterns, thereby confirming its importance in ecological and environmental research. Additionally, land use and land cover (LULC) patterns and change detection study has become a valuable tool in understanding the critical role of land resources in achieving environmental security and sustainable development (Iduseri et al., 2024). LULC classification have evolved over the years by incorporating various machine learning algorithms, such as random forest (RF), support vector machine (SVM), maximum likelihood classification (MLC) and K-nearest neighbor algorithm (KNN) (Talukdar et al., 2020; Hussain et al., 2025). Among various machine learning approaches, SVM learning is preferable due to their distinct approach to classification. Unlike other methods, SVM aims to maximize the margin—the distance from the decision boundary to the nearest data points of all classes. It is well-suited for handling complex relationships within the data, without requiring extensive pre-processing or transformations from the user. Furthermore, SVM often provides more accurate classifications especially with smaller complex datasets compared to other algorithms.

The Northeastern Region (NER) of India comprises several states rich in natural forest cover. The NER has approximately 65% forest cover of its total geographical area. In 2001, about 122,400 km^2 of forest was reclaimed, reducing the forest cover to 46% (Das, 2015). Such depletion of forest cover in NER is primarily linked to human activity (Marchang, 2021). The loss of vegetation due to deforestation highlights the need for systematic assessment to understand its impacts on environmental sustainability. Since the change in forest cover could lead to ecological, social, and economic impacts, including biodiversity loss, the extinction of biotic communities, rising land surface temperatures, and desertification (Saikia et al., 2024). The expansion of urban areas has a great impact on the environment, driven by the alteration of natural habitats and landscape features (Roy et al., 2022). Urban expansion is primarily driven by the socio-economic and physical factors, including demographic and economic growth. However, socio-economic development has a significant impact on urban expansion than over-population in which fastest expansion of the cities degrades landscape patterns and raises concerns about climate change, food security and natural resources scarcity (Liu et al., 2018; Liu et al., 2021; Roy et al., 2022).

Meghalaya, in NER of India, is a house to a wide variety of plant life, including tropical rainforests, grasslands, bamboo groves, and medicinal plants (Singh, 2010). Preserving this diverse vegetation plays a vital role in preserving ecological balance, supporting local livelihoods, and safeguarding the well-being of the region's unique plant and animal life (Rawal et al., 2013). The East Khasi Hills district is centrally located within the state of Meghalaya, and Shillong city as its capital. Shillong city has undergone LULC transformations at an unprecedented rate; such transformations have resulted in environmental changes, including rising land surface temperatures (Saikia et al., 2024). Therefore, monitoring forest cover dynamics will inform authorities of any changes to the forest and help them adopt policies to manage the environment sustainably.

To simulate spatiotemporal changes in the East Khasi Hills, an integrated Cellular Automata-Artificial Neural Network (CA–ANN) model using modules for land use change simulation and evaluation (MOLUSCE) was employed (Islam et al., 2023). MOLUSCE is a widely used plugin that can effectively compute LULC change,

assess spatiotemporal changes, predict transition prospects and simulate future scenarios (Islam et al., 2023; Baghel et al., 2024). The CA component models spatial land use changes based on local interactions, while the ANN predicts land use transitions by learning from historical data (Gantumur et al., 2020). The MOLUSCE framework combines these approaches to simulate both the spatial distribution and temporal dynamics of land use changes, providing insights into the factors influencing land use patterns.

This study specifically examined the impact of urbanization on LULC changes and forest cover dynamics from 2002 to 2022 and predicted the future LULC of 2030 and 2040 using the SVM classification and CA–ANN model for prediction.

2 Study area

East Khasi Hills is a district in the state of Meghalaya, located in the northeastern part of India (**Fig. 1**). It lies in the south-central region of Meghalaya, covering a total area of 2,748 km^2. The district is situated approximately between 25°10' and 25°40' N latitude and 91°20' and 92°10' E longitude. It is bordered by Bangladesh to the south, West Jaintia Hills to the east, Ri-Bhoi to the north, and West and South West Khasi Hills to the west.

East Khasi Hills has two subdivisions: Shillong Sadar, with its headquarters in Shillong, and Sohra, with its headquarters in Sohra (Cherrapunjee). The district comprises of eight community and rural development (C & RD) blocks and is the most densely populated

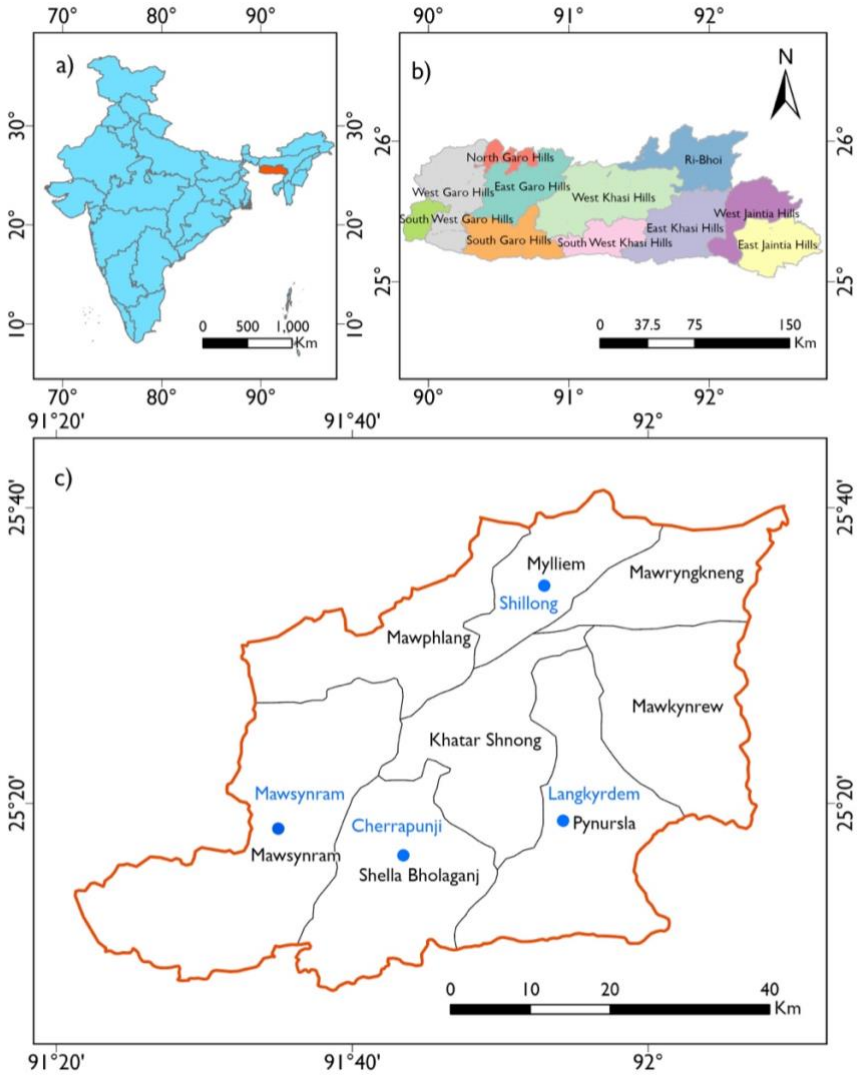

Figure 1. *Map of the study area showing a) the state of Meghalaya in India (highlighted in red), b) the district boundary of the state of Meghalaya, and c) East Khasi Hills district including eight community and rural development blocks.*

district in the state (**Fig. 1**). The climate varies across the study area, ranging from temperate in the plateau areas to warmer tropical and subtropical conditions in the northern and southern parts (KVK, 2020). The average temperature ranges between 2°C during winter months (October to March) and 25°C during summer months (May to October). The average annual rainfall of about 2,000 mm, mostly occurs during the monsoon season (June to September), constituting the region's water resources.

3 Materials and methods

3.1 Satellite imageries and ancillary data

This study utilized high-resolution satellite imagery (30-meter resolution) from Landsat 7 (Enhanced Thematic Mapper Plus) for 2002, and Landsat 8 (OLI/TIRS C2 L2) for 2013 and 2022. The satellite imageries and the shuttle radar topography mission (SRTM) digital elevation model (DEM) were obtained from the USGS Earth Explorer website (USGS, 2024). To minimize the seasonal effect on the satellite images, composite images with less than 10% cloud cover were selected. Detailed information about the data used in this study is presented in **Table 1**.

Block-wise population data were collected from the 2011 Census of India datasets (Census, 2011). Based on the population data, all C & RD blocks in the East Khasi Hills district were categorized. Road data were obtained from Open Street Map (OSM, 2024), and the analysis was performed in ArcGIS 10.4 using the Euclidean distance in the Spatial Analyst extension.

3.2 Data processing

The satellite imageries were processed using ArcGIS 10.4, ERDAS Imagine 2014, and QGIS 2.16 software to create maps for NDVI, LULC, slope, aspect, and elevation. Land use and land cover data was extracted using a supervised classification method in ArcGIS 10.4, applying a SVM classification method. The recoding was performed in ERDAS Imagine 2014. Seven land use classes were identified, such as dense forest, moderate forest, agriculture, fallow land, settlement, sand bar, and water body. Three sets of satellite images from 2002, 2013, and 2022 were used for LULC classification and further used to analyze how land use classes were changed over the years in the study area using the following predictor variables, such as slope, aspect, elevation, population density, and distance to roads (**Fig. 2**). Population data were converted into raster format based on the total population in each administrative block. Euclidean distances were computed for roads to make continuous raster data.

The NDVI was calculated using the following formula:

$$\mathrm{NDVI} = \frac{NIR - RED}{NIR + RED}$$

In remote sensing, "RED" refers to reflectance in the visible red spectrum, while "NIR" refers to reflectance in the near-infrared spectrum. The NDVI value ranges from -1 to +1, where higher values indicate

Table 1. *The details of satellite imagery and other datasets used in this study.*

Data	Sensor	Date of acquisition	Resolution (m)	Source
Landsat 7	ETM+ C2 L2	8 October 2002, 16 November 2002	30	United States Geological Survey (USGS, 2024)
Landsat 8–9	OLI/TIRS C2 L2	7 November 2013, 23 November 2013	30	USGS, 2024
Landsat 8–9	OLI/TIRS C2 L2	23 November 2022, 24 November 2022	30	USGS, 2024
SRTM DEM	N/A	N/A	30	USGS, 2024
Population	N/A	N/A	N/A	Census, 2011
Road network	N/A	N/A	N/A	Open Street Map (OSM, 2024)

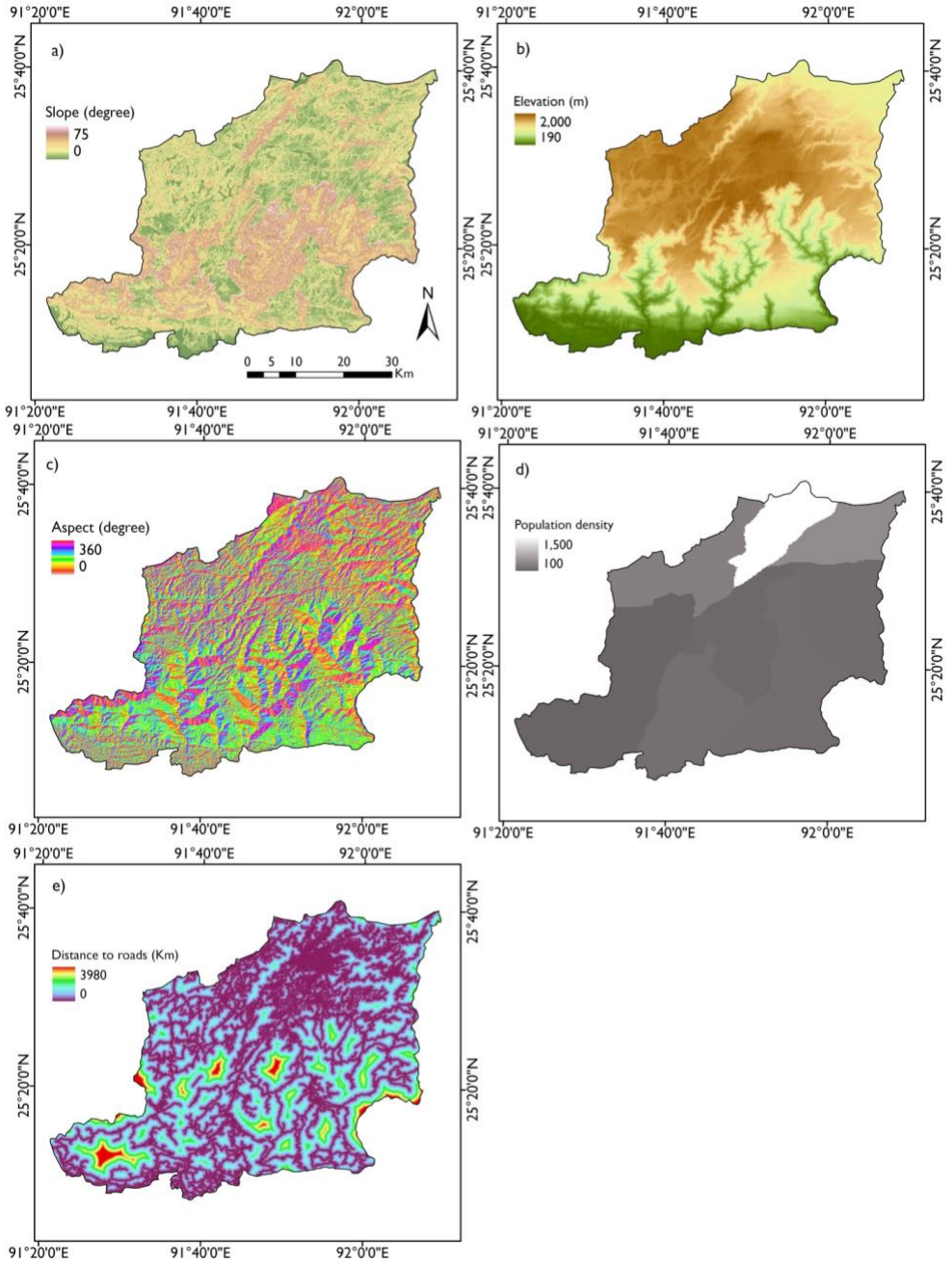

Figure 2. *Spatial distribution of explanatory variables: a) Slope, b) Elevation, c) Aspect, d) Population density, and e) Distance to roads.*

denser vegetation coverage and lower values indicate sparse or no vegetation coverage (Nath and Acharjee, 2013).

3.3 LULC change analysis and transition potential modelling

The LULC changes were analyzed using a post-classification change detection study by employing a change matrix. The change matrix depicts the LULC transition for each time period starting from 2002 to 2022. The MOLUSCE plugin was used to estimate spatiotemporal changes and calculate the LULC transitions between the studied intervals (2002 to 2013 and 2013 to 2022). These results were used to create predicted LULC maps for 2030 and 2040. The area changes and transition probability matrix were calculated using LULC, elevation, slope, aspect, distance

to roads, and population density as explanatory variables. These factors are commonly used in LULC change analysis as they provide consistent data on both the physical and anthropogenic drivers of LULC dynamics (Islam et al., 2023).

The MOLUSCE plugin offers four transition modelling methods, for example Artificial Neural Network (ANN), Weight of Evidence (WoE), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE) to produce potential transition maps. Elevation, slope, aspect, distance to roads and population density were considered key determinants influencing future land cover transitions. The MOLUSCE approach uses a multilayer perception neural network with neighborhood analysis to model transition potentials and derive transition rules based on historical LULC changes (Islam et al., 2023). In the ANN learning process, transition rules were learned through 100 iterations, using a 3×3 pixel neighbourhood, a learning rate of 0.001, four hidden layers, and a momentum values of 0.05 for the 2022 LULC dataset.

3.4 Prediction and model validation

To predict LULC transitions for 2030 and 2040, five key independent variables, slope, aspect, elevation, population density, and distance to roads, were integrated into the MOLUSCE plugin along with potential LULC maps. Model validation was performed using CA–ANN techniques within the MOLUSCE plugin to model transition potentials and simulate future land use (Gantumur et al., 2020; Islam et al., 2023). The step-by-step analysis of LULC classification and prediction is given in the flowchart (**Fig. 3**).

To validate the model and assess prediction accuracy, the LULC of 2022 was predicted using

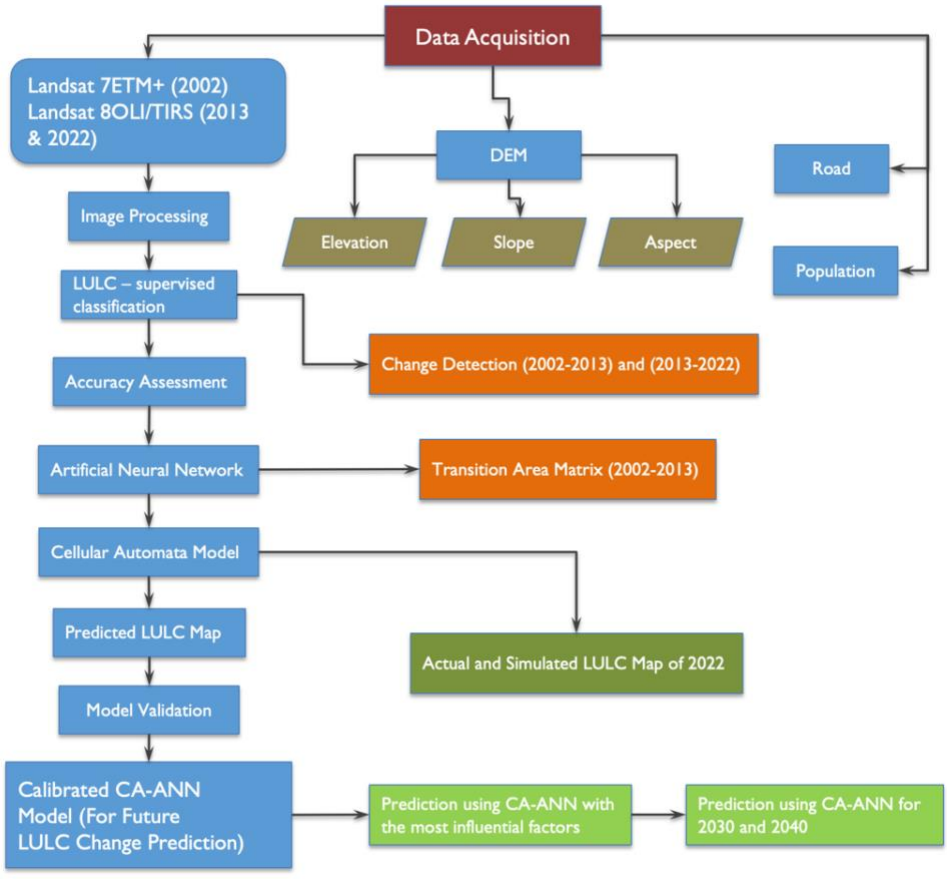

Figure 3. *Flowchart showing the step-by-step analysis of Land Use and Land Cover (LULC) and their prediction using Cellular Automata–Artificial Neural Network (CA–ANN).*

explanatory variables and transition matrices based on LULC data from 2002 and 2013. The MOLUSCE plugin also provide a *Kappa* validation score and enables a comparison between actual and projected LULC classification results.

4 Results and discussion

4.1 NDVI values for the year 2002, 2013, and 2022

The NDVI values range from -0.14 to 0.61 in 2002, -0.18 to 0.62 in 2013, and -0.16 to 0.69 in 2022. The NDVI values were categorized into five classes, e.g., very low, low, moderate, high, and very high. The very low class consists of values <0; the low class ranges from 0 and 0.2; the moderate class ranges from 0.2 and 0.4; the high class ranges from 0.4 to 0.6; and the very high class includes values >0.6. From 2002 to 2022, the combined area under the low and very low NDVI classes steadily increased from 37 km^2 in 2002 to 227 km^2 in 2013, and then to 543 km^2 in 2022, indicating a substantial presence of non-vegetated and sparsely vegetated areas (**Fig. 4**). Moderate NDVI class was also increased its area between 2002 and 2013 (from 1,644 km^2 to 2,047 km^2) but declined to 1,971 km^2 in 2022. On the contrary, the combined area of the high and very high NDVI classes showed a sharp decline from 1,160 km^2 in 2002 to 568 km^2 in 2013, and further to 327 km^2 in 2022. These changes may be attributed to human activities that led to the sharp decline in vegetation cover, typically driven by the conversion of forests to agriculture, settlements, and other urban developmental areas. Zhang et al. (2023) highlighted that differences in NDVI values typically occur across different land cover types due to variations in the constituent objects present within those regions. For instance, trees are found along rivers, roads, and between houses in settlement areas, while some trees are present in agricultural fields, fallow land, grasslands and shrublands.

The observed NDVI values reveal a clear pattern in our study area. The areas under very low NDVI classes correspond to highly urbanized zones with minimal vegetation, encompassing roads, buildings, and dense settlements such as the Shillong cantonment region (**Fig. 4**). Low NDVI class signifies sparse vegetation,

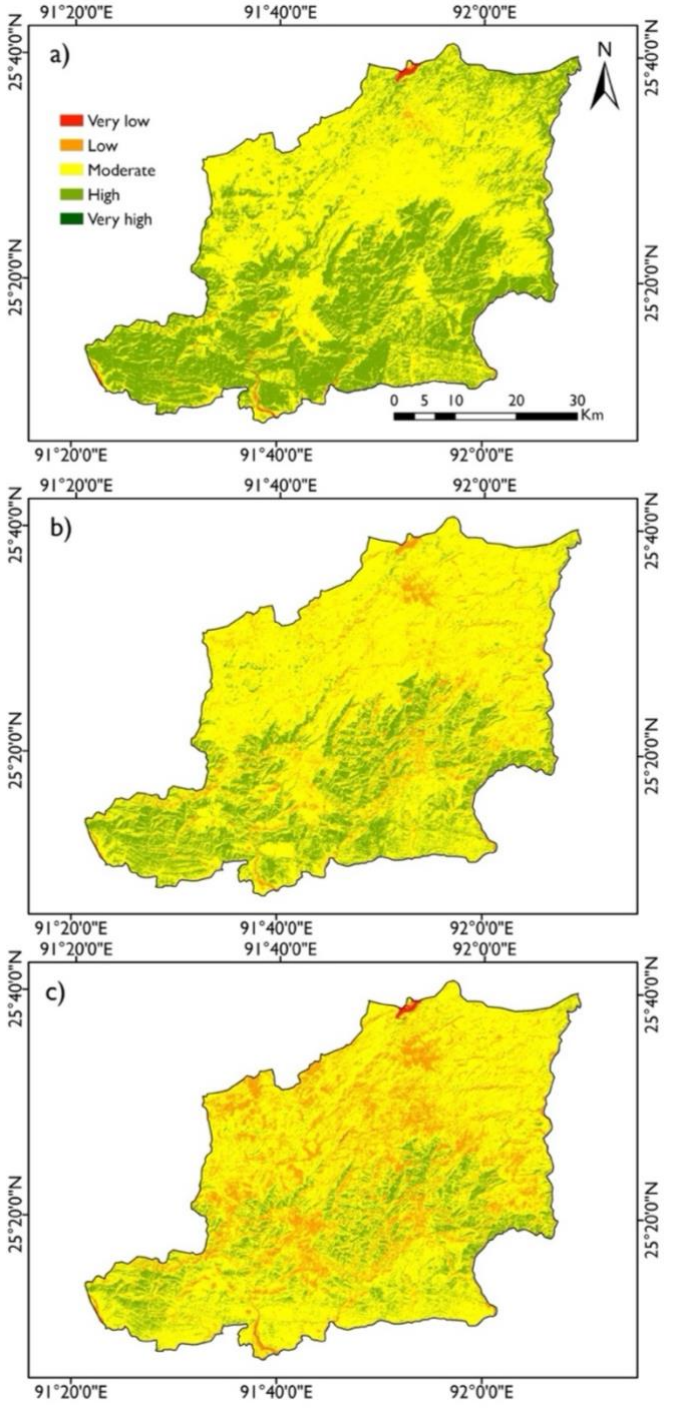

Figure 4. *Comparison of NDVI values in East Khasi Hills district, Meghalaya, India, for the years: a) 2002, b) 2013, and c) 2022.*

encompassing bare ground, and scattered greenery within built-up areas. Moderate NDVI represents areas with higher vegetation density, including individual trees, gardens, and green patches along roads and settlements. High NDVI indicates dense vegetation, such as community-owned forests and tree-covered lands. Very high NDVI corresponds to the most vegetated areas, such as dense forests. High and very high NDVI classes are primarily located in the southern part of the study area, within the rugged terrain (**Fig. 4**). Our results show a steady increase in non-vegetated areas represented by very low, low and moderate NDVI classes and a sharp decline in high and very high NDVI classes from 2002 to 2022, potentially linked to human activities. These changes highlight the potential role of anthropogenic activities on vegetation dynamics (Gao et al., 2022).

4.2 Accuracy assessment

Accuracy assessment is a crucial component of LULC classification (Mas, 1999; Nath et al., 2021). It evaluates how well the LULC classification performed compared to what was on the ground and also assess the methodology for identifying any potential errors (Paul, 2022; Islam et al., 2023). A stratified random sampling method was used to assess the accuracy of the LULC classes, utilizing the classification and segmentation tools in the Spatial Analyst package of ArcGIS. The results were verified through historical imagery from Google Earth Pro and ground truthing. The results show that the overall accuracy of the classified images for the years 2002, 2013, and 2022 were greater than 85%, with corresponding *Kappa* coefficients exceeding 0.75. These results agree well with the reported global accuracy range of 85–90% for LULC mapping (Nath et al., 2021). Uddin et al. (2023) reported a similar accuracy of 86% and a *Kappa* coefficient of 0.83 for future LULC predictions using CA–ANN model. Thus, our accuracy assessment is consistent with stablished benchmarks in the field.

4.3 LULC classification and change detection

The results of LULC classification are presented in **Table 2**. The data showed that the dense forest had experienced an overall decline of 33 km^2 in area between 2002 and 2022, reflecting continued deforestation despite conservation practices. Moderate forest initially expanded between 2002 and 2013 but subsequently declined by 77 km^2 in 2022. Agricultural land showed an increasing trend from 2002 to 2022, likely due to shifting cultivation and land reclamation. Water bodies exhibited minor fluctuations, with an overall increase of 9 km^2 between 2000 and 2022. Fallow land had decreased by 85 km^2 during the same time period. Meanwhile, sand bars remained relatively stable, showing only a minor change, suggesting minimal changes in sedimentation pattern.

The LULC changes from 2002 to 2022 showed transformations in forest cover, urban expansion, and agricultural land (**Fig. 5**). Dense forest experienced a drastic decline from 1,480 km^2 in 2002 to 828 km^2 in 2013, suggesting widespread deforestation, likely driven by logging, conversion to moderate forests, and agricultural expansion. However, by 2022, dense forest partially recovered to 1,447 km^2, indicating positive effects of conservation efforts (Mir et al., 2022). Similarly, moderate dense forest saw an initial expansion from 567 km^2 in 2002 to 1,382 km^2 in 2013, followed by a decline to 490 km^2 in 2022, which may suggest

Table 2. *Land use and land cover change in East Khasi Hills from 2002 to 2022.*

LULC categories	2002		2013		2022	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Dense forest	1,480	52	828	29	1,447	51
Sand bar	8.0	0.28	5.0	0.18	7.0	0.25
Fallow land	459	16	281	9.9	374	13
Water body	25	0.88	22	0.77	34	1.2
Settlement	57	2.0	67	2.4	87	3.0
Moderate forest	567	20	1,382	49	490	17
Agriculture	245	8.6	256	9.0	402	14

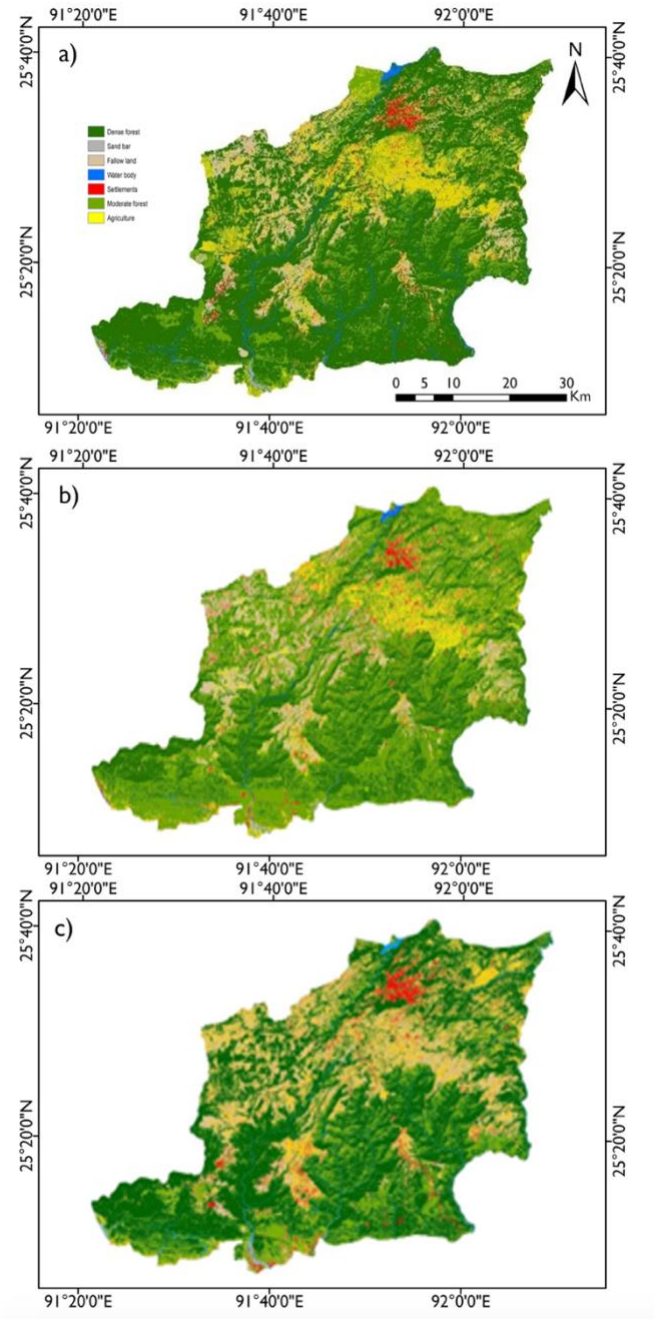

Figure 5. *Land use and land cover maps for the years: a) 2002, b) 2013, and c) 2022.*

deforestation of secondary forests or degradation due to anthropogenic pressures, urban expansion and agricultural practices. Some of the major changes in LULC have noticeably occurred in the southwest and southeast of the study area, especially in Mawsynram, Cherrapunji, and Langkyrdem. These sites are well known for their tourist attractions.

A steady increase in built-up areas, which grew from 57 km^2 in 2002 to 87 km^2 in 2022, indicating a steady urbanization driven by population growth, infrastructure development, and economic activities (Dolui and Chakraborty, 2024). This trend aligns with urbanization patterns in the study area, where natural landscapes are converted into residential and industrial zones, leading to habitat fragmentation and loss of green cover (Saikia et al., 2024). Water bodies have also undergone significant changes, as the total waterbody area increased from 25 km^2 in 2002 to 34 km^2 in 2022. This increase could be temporarily attributed to hydrological changes, and climatic variability. The expansion of agricultural land also follows a steady increasing trend; from 245 km^2 in 2002 to 256 km^2 in 2013, and then to 402 km^2 in 2022. Additionally, fallow land exhibited a steady decreasing trend, decreasing to 281 km^2 in 2013, before settling at 374 km^2 in 2022, reflecting changes in cultivation cycles, shifting agricultural priorities, jhum cultivation, and possible land degradation (Baghel et al., 2024). The sand bar remained relatively stable, with a minor decrease from 8 km^2 in 2002 to 7 km^2 in 2022, indicating minimal changes in river sedimentation and a stable fluvial environment.

4.4 Model validation and LULC prediction

The predicted LULC classes were validated against satellite-derived data by comparing the contents of both data sources and analyzing the characteristics of the observed and simulated LULC classifications. The comparison of satellite-derived land cover data with the predicted LULC data for 2022 resulted in a *Kappa* validation score of 0.79, an overall correctness of 86.72%, and a *Kappa* histogram value of 0.82, indicating a strong model performance (Baghel et al., 2024). Predictions for 2030 were made using LULC data from 2013-2022. Then, using the same explanatory variables (slope, aspect, elevation, population density, and distance to roads) and a transition matrix, LULC for 2040 was predicted based on 2022-2030 LULC data.

Table 3. *Predicted land use and land cover change in East Khasi Hills for 2030 and 2040.*

LULC categories	2030		2040	
	Area (km²)	Area (%)	Area (km²)	Area (%)
Dense forest	1,200	42	1,172	41
Sand bar	32	1.1	82	2.9
Fallow land	197	6.9	126	4.4
Water body	15	0.53	15	0.53
Settlement	118	4.2	175	6.2
Moderate forest	1,046	37	1,023	36
Agriculture	233	8.2	248	8.7

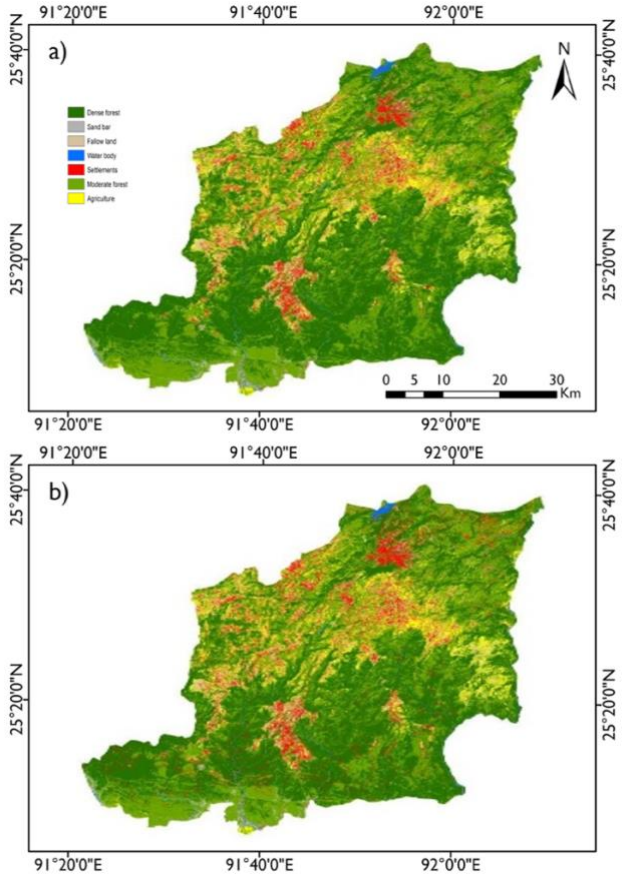

Figure 6. *Predicted land use and land cover maps for the years: a) 2030, and b) 2040.*

The predicted LULC classes revealed a decreasing trend for dense forest from 51% to 41% in total area between 2022 and 2040 (**Table 3**). A steady increase in deforestation was observed, especially between 2022 and 2030, as shown in the predicted results (**Fig. 6**). Such a decline could be linked to the continued urban development and other economic activities. Fallow land had also decreased, which could be linked to the efforts by the government and other organizations working on forest restoration in East Khasi Hills. In some cases, vegetation may have recovered with time and likely converted to moderate forests. Water bodies were decreased slightly, which could be associated with the rise in land surface temperature and dying up of rivers and lakes (Saikia et al., 2024). Settlements had predicted to increase rapidly from 2022 to 2040, which could likely follow the rise in population density. Moderate forest increased from 490 km^2 (17%) to 1,023 km^2 (36%). Agricultural land showed a decreasing trend during 2022 to 2040 (from 402 km^2 to 248 km^2). These changes may be attributed to an increase in the population, which likely resulted in greater exploitation of dense forests, converting them into moderate forests and eventually into settlements. The results indicate a major change in forest cover over the 30-year period, driven primarily by increasing demand for land, timber, and tourist activities, which has likely contributed to land use transformation across the study area.

5 Conclusion

This study highlights the impact of urbanization on LULC changes and forest cover dynamics in East Khasi Hills district, Meghalaya, India. The decline in dense forest, coupled with the fluctuating trends in moderate forest and agricultural land, suggests a complex interplay between conservation efforts and land reclamation. The predicted LULC for 2030 and 2040 suggests a continued development of built-up areas, primarily due to increasing demand. A sustainable approach must be adopted to

minimize the long-term impact of these changes on the environment. Further investigation using additional data and models is recommended to provide planners and policymakers with a clearer insight into LULC changes and their effects on the environment to ensure sustainability.

6 Data availability statement

The data is presented in the manuscript as figures and tables. The data can be made available upon request from the corresponding author.

7 Author contributions

P. Saikia: conceptualization, supervision, writing – original draft, and writing – review & editing. D.S. Langshiang: data curation, formal analysis, and writing – original draft. L. Raliang: formal analysis, visualization, and writing – original draft. All authors approved the final version of the manuscript.

8 Conflict of interest

The authors declare no conflict of interest related to this study.

9 Ethical statement

This study does not require ethical approval.

10 Copyright statement

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